

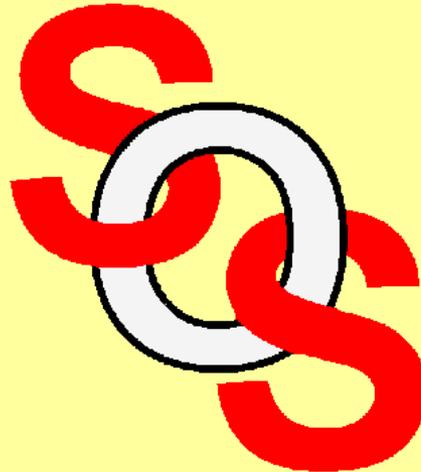
NEW DIRECTIONS IN MODEL DEVELOPMENT FOR RF/MICROWAVE COMPONENTS AND DEVICES UTILIZING NEURAL NETWORKS AND SPACE MAPPING

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Artificial Neural Network (ANN) Modeling

Artificial Neural Networks are suitable in modeling high-dimensional and highly nonlinear problems

ANN models are computationally efficient and can be more accurate than empirical models

multilayer feedforward networks can approximate any measurable function to any desired level of accuracy, provided a deterministic relationship between input and target exists
(*White et al., 1992*)

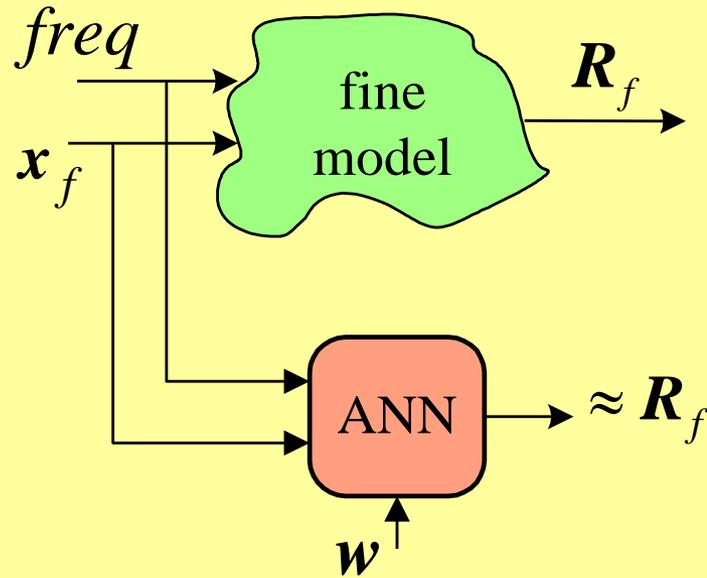
ANNs that are too small cannot approximate the desired input-output relationship

ANNs with too many internal parameters perform correctly in the learning set, but give poor generalization ability

ANNs are suitable models for microwave circuit optimization and statistical design
(*Zaabab, Zhang and Nakhla, 1995, Gupta et al., 1996, Burrascano and Mongiardo, 1998, 1999*)



Classical Neuromodeling of Microwave Components



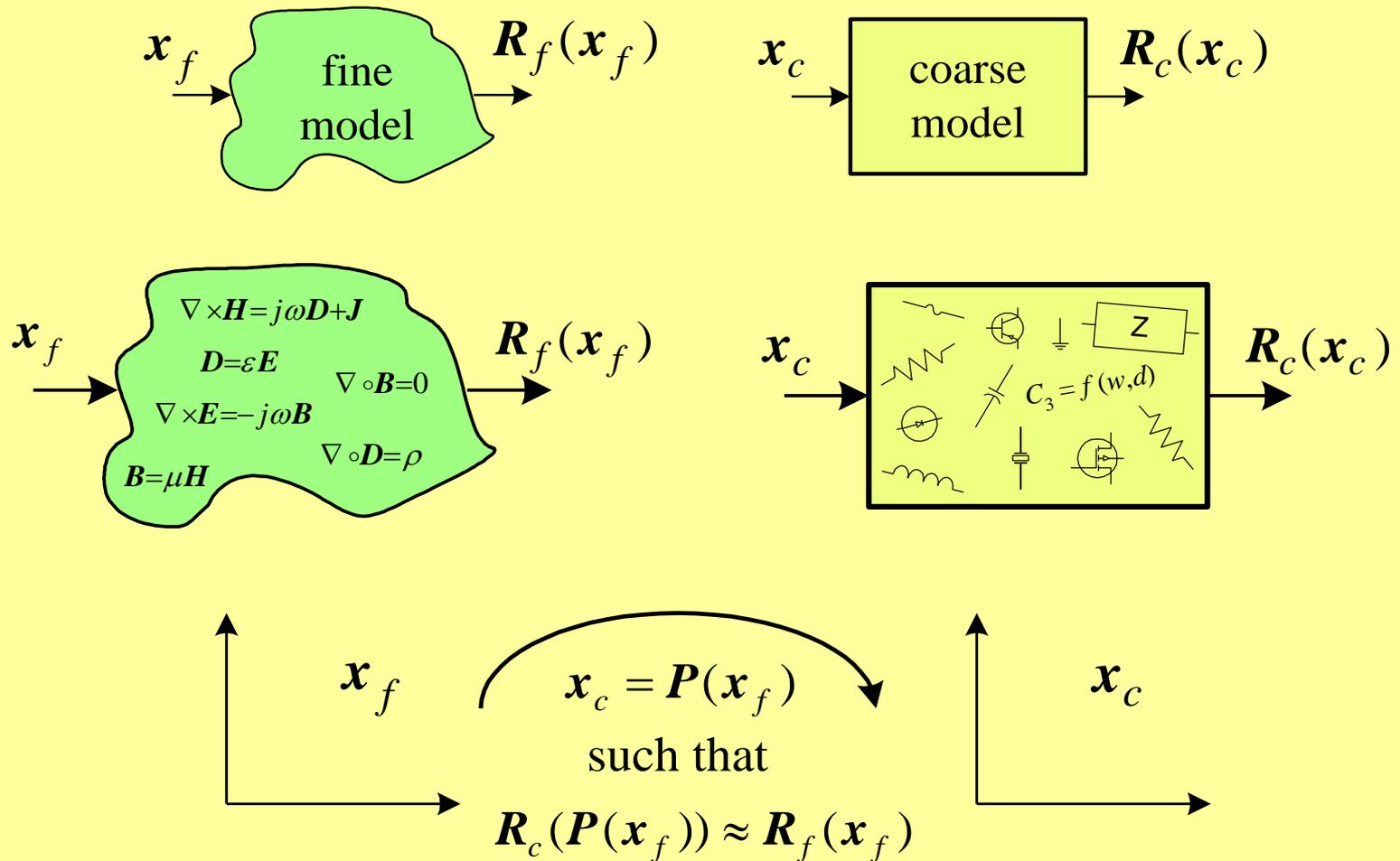
many learning samples are usually needed to ensure model accuracy

the number of learning samples needed to approximate a function grows exponentially with the ratio of the dimensionality to the function's degree of smoothness (*Stone, 1982*)

even with sufficient training data, the reliability of MLPs for extrapolation may be very poor



The Aim of Space Mapping (Bandler et al., 1994-)

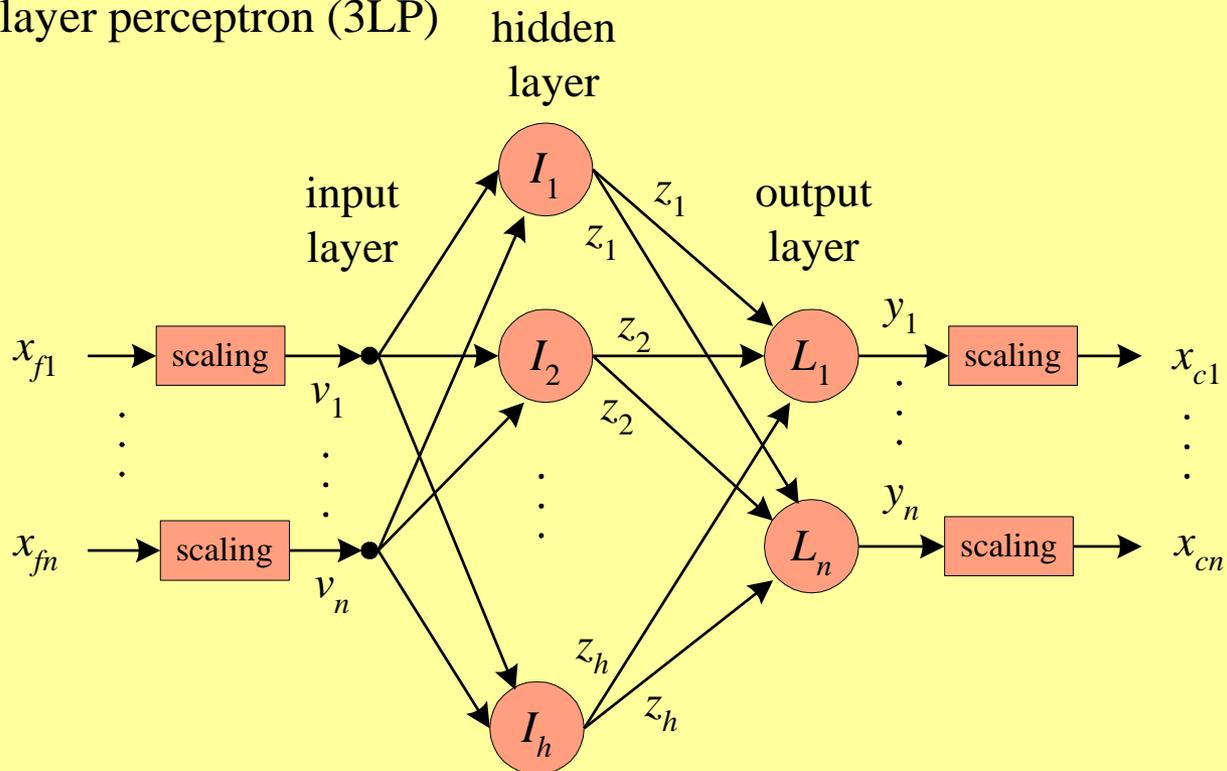




Neural Space Mapping

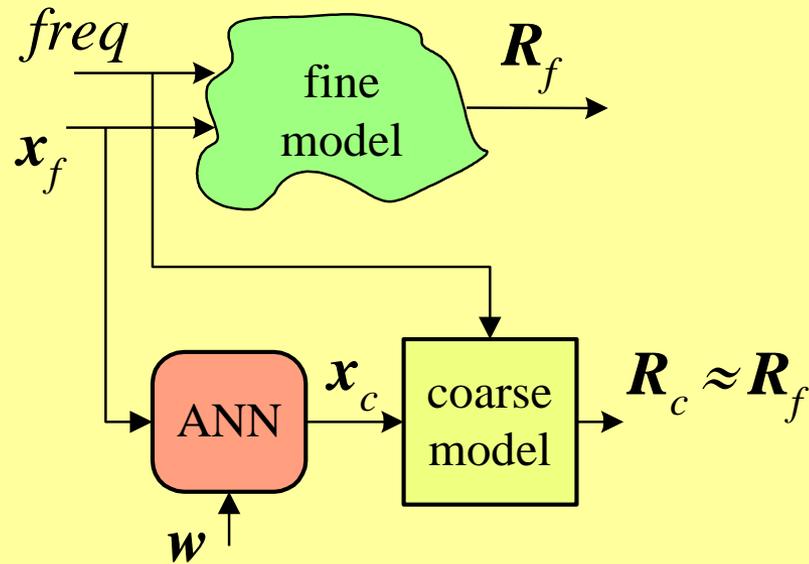


using a three layer perceptron (3LP)

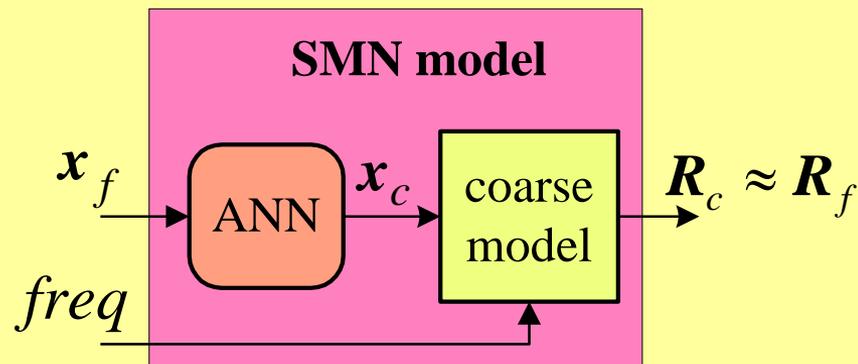




Space Mapped Neuromodeling (SMN) Concept

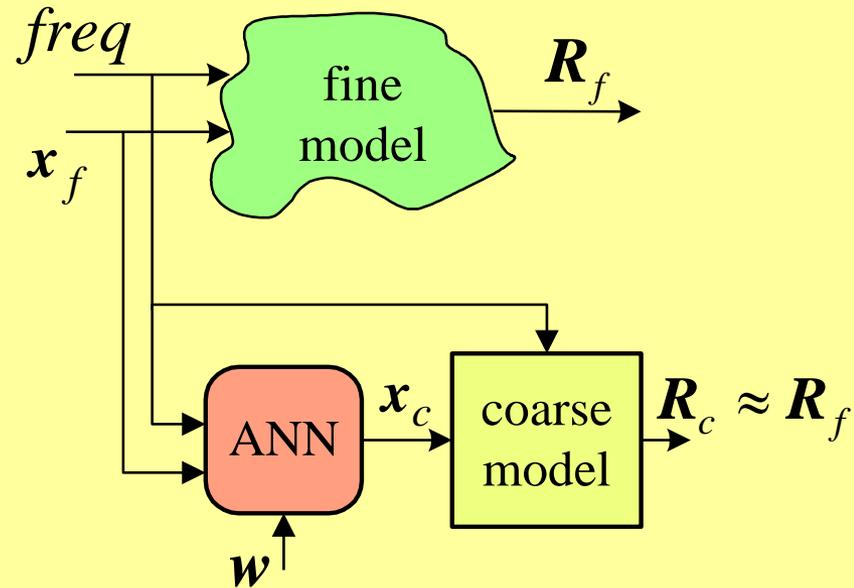


once the ANN is trained

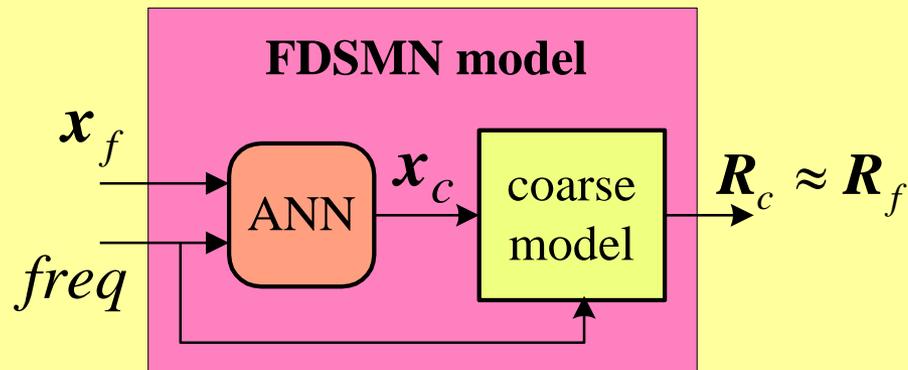




Frequency-Dependent Space Mapped Neuromodeling (FDSMN) Concept

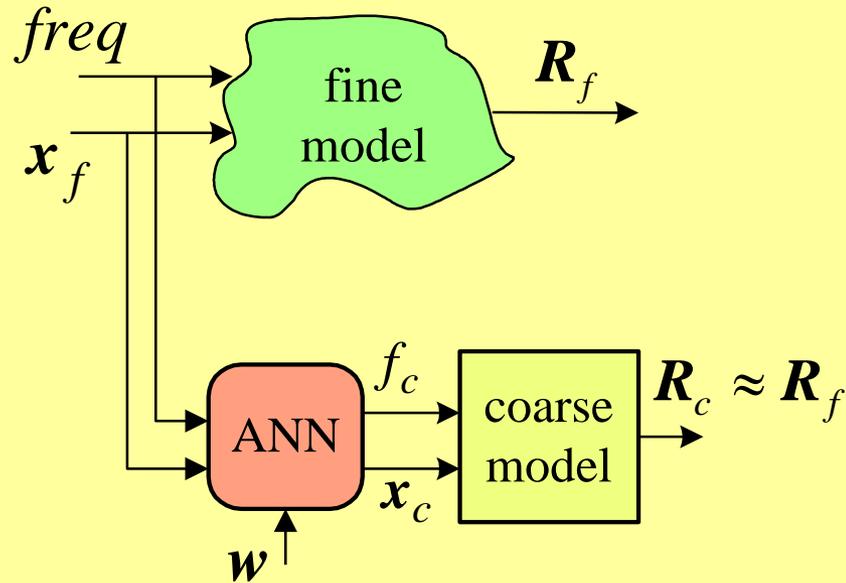


once the ANN is trained

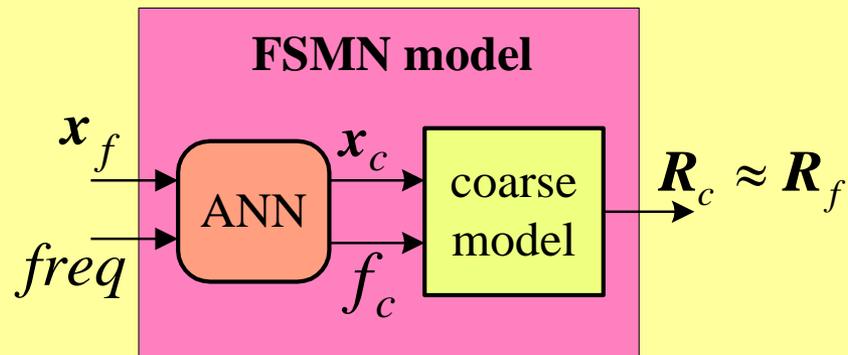




Frequency Space Mapped Neuromodeling (FSMN) Concept

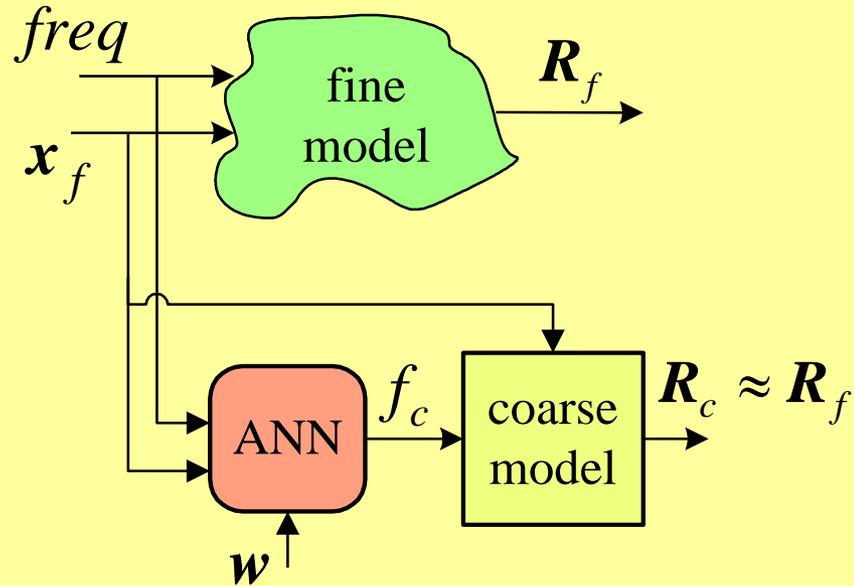


once the ANN is trained

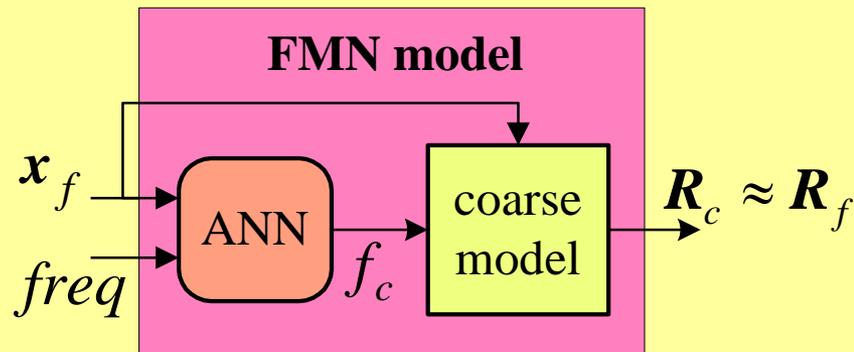




Frequency Mapped Neuromodeling (FMN) Concept

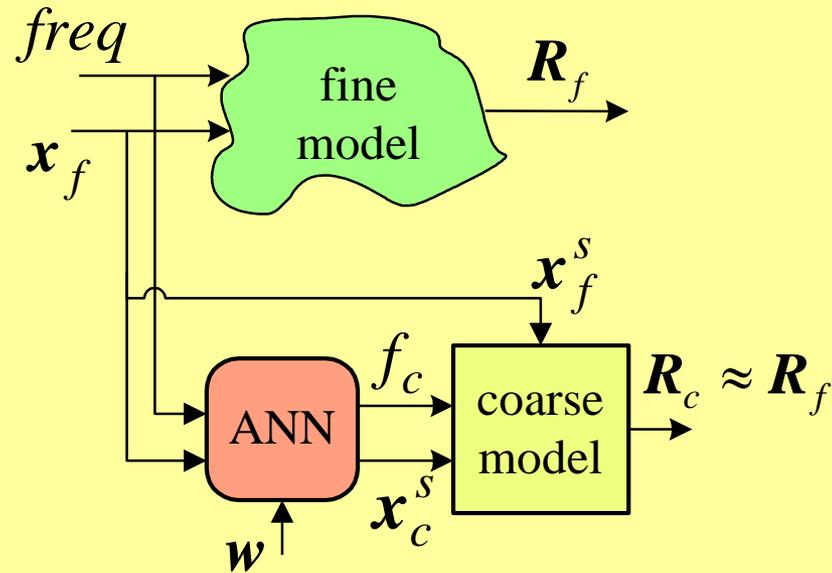


once the ANN is trained

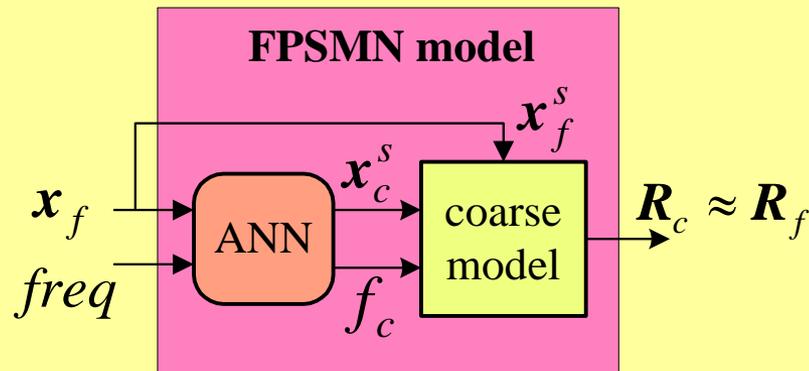




Frequency Partial Space Mapped Neuromodeling (FPSMN) Concept



once the ANN is trained





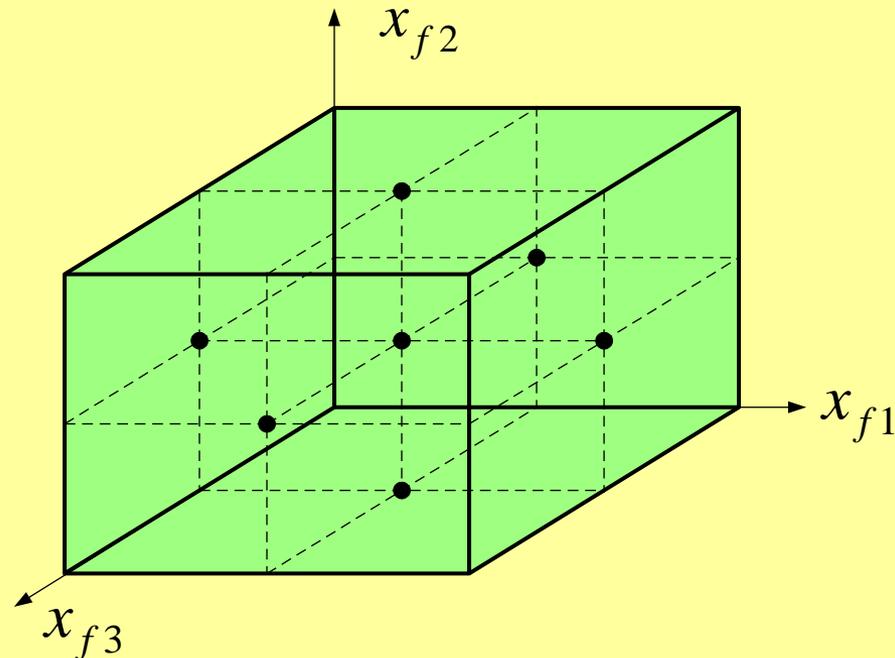
Starting Point and Learning Samples

we chose a unit mapping ($\mathbf{x}_c \approx \mathbf{x}_f$ and $f_c \approx freq$) as the starting point for training

to keep a reduced set of learning data samples, we consider an n -dimensional star distribution for the learning base points (*Bandler et al., 1989*)

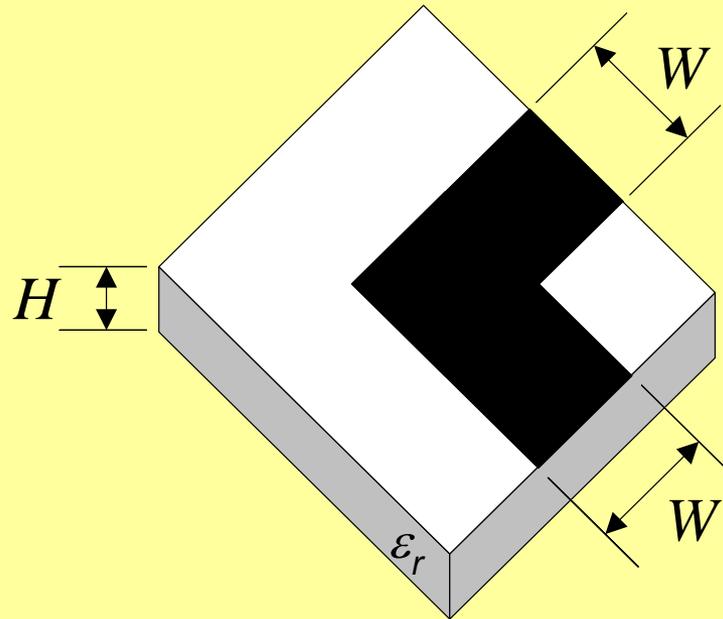
the number of learning base points for a microwave circuit with n design parameters is

$$B_p = 2n + 1$$





Microstrip Right Angle Bend



region of interest

$$20\text{mil} \leq W \leq 30\text{mil}$$

$$8\text{mil} \leq H \leq 16\text{mil}$$

$$8 \leq \epsilon_r \leq 10$$

$$1\text{GHz} \leq \text{freq} \leq 41\text{GHz}$$

“coarse” model: Gupta model (*Gupta, Garg and Bahl, 1979*)

“fine” model: Sonnet’s *em*TM

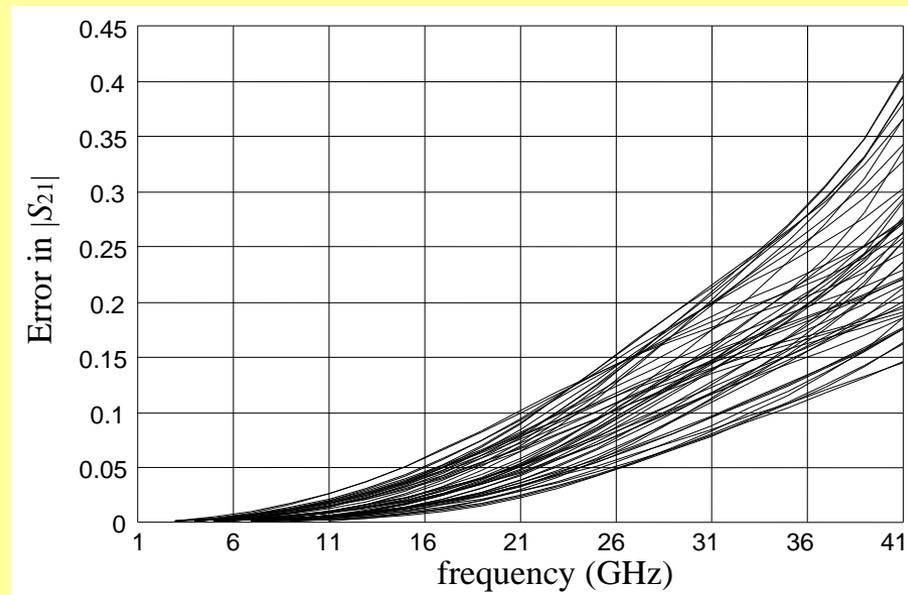
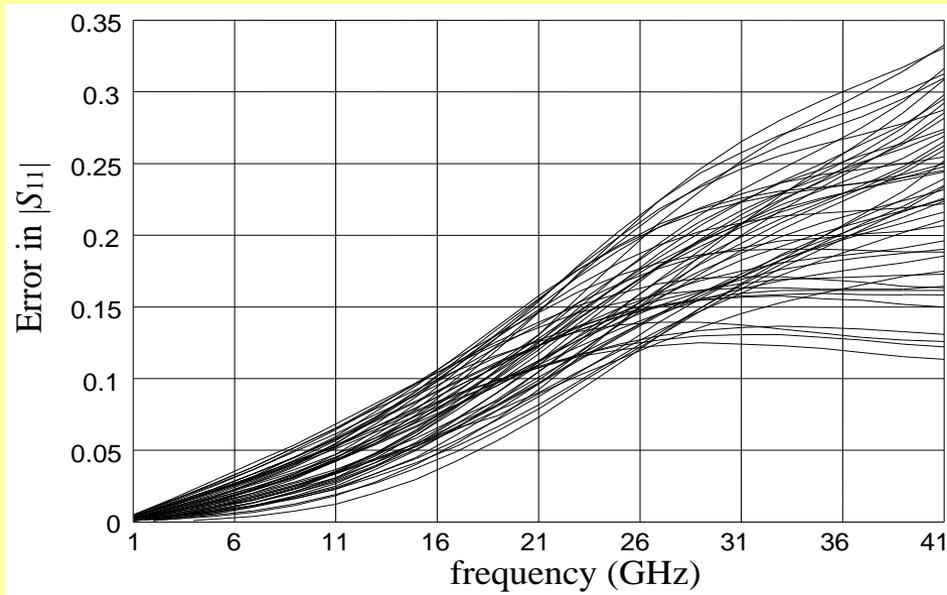
learning set: 7 base points with “star” distribution

testing set: 50 random base points in the region of interest



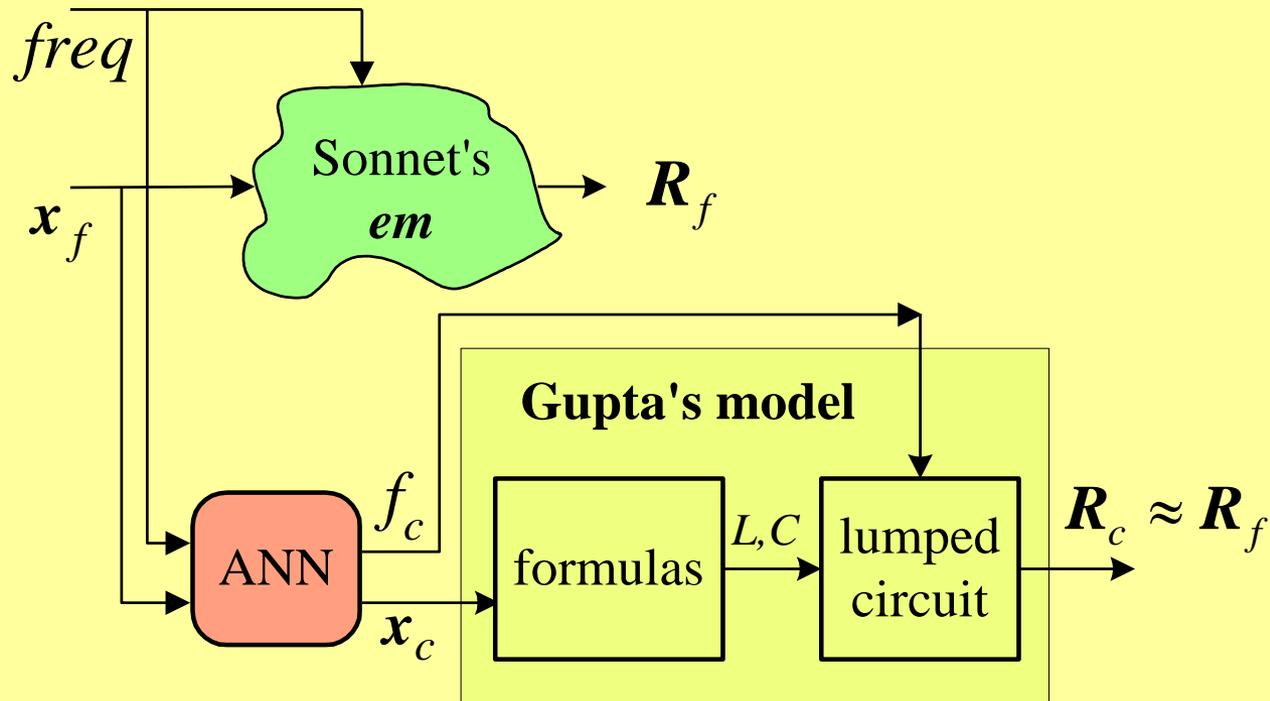
Microstrip Right Angle Bend Response Errors

comparison before neuromodeling between *em*TM and Gupta model at 50 random test points





FSMN Model for the Right Angle Bend (3LP:4-8-4)

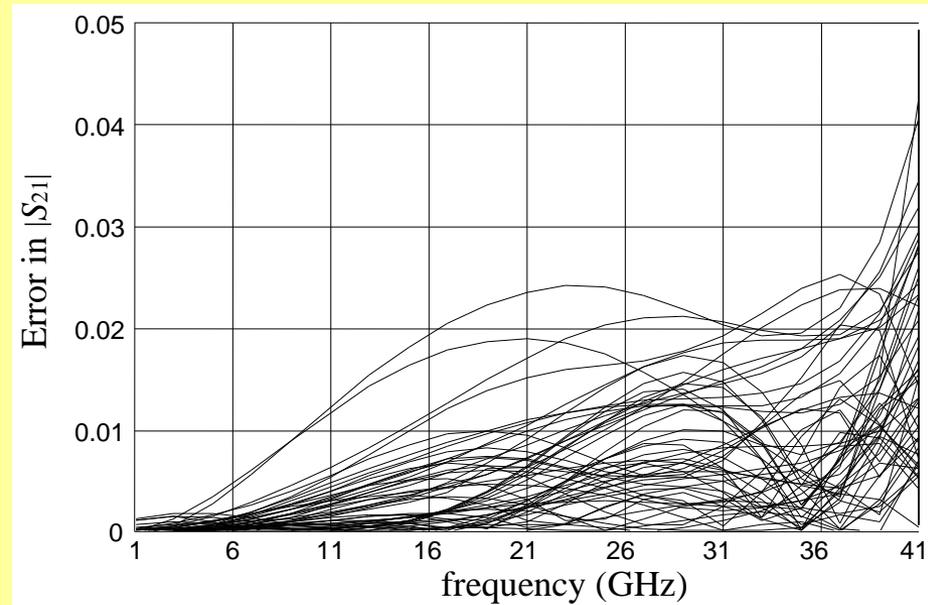
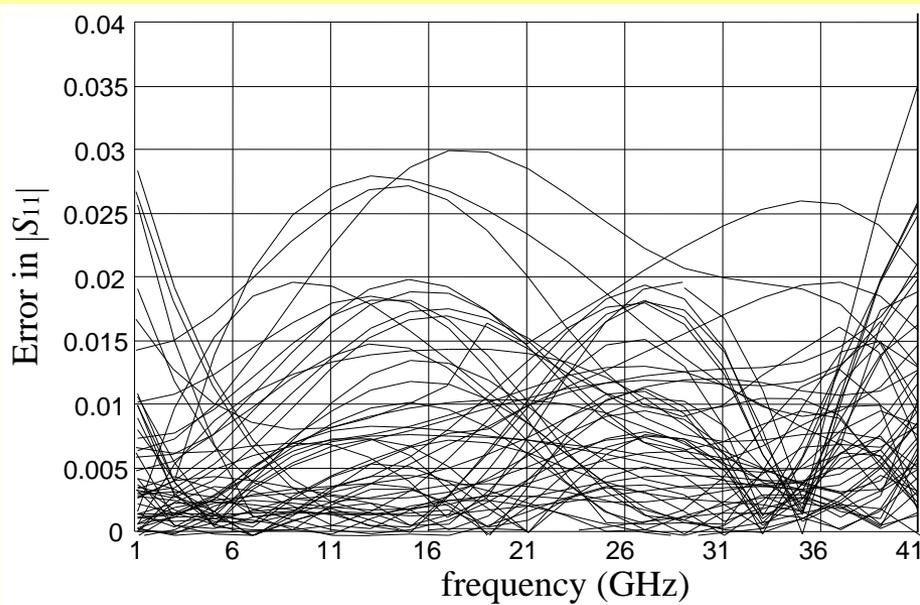


implementation: an OSA90/hopeTM child program simulates the coarse model at a different frequency variable through Datapipe



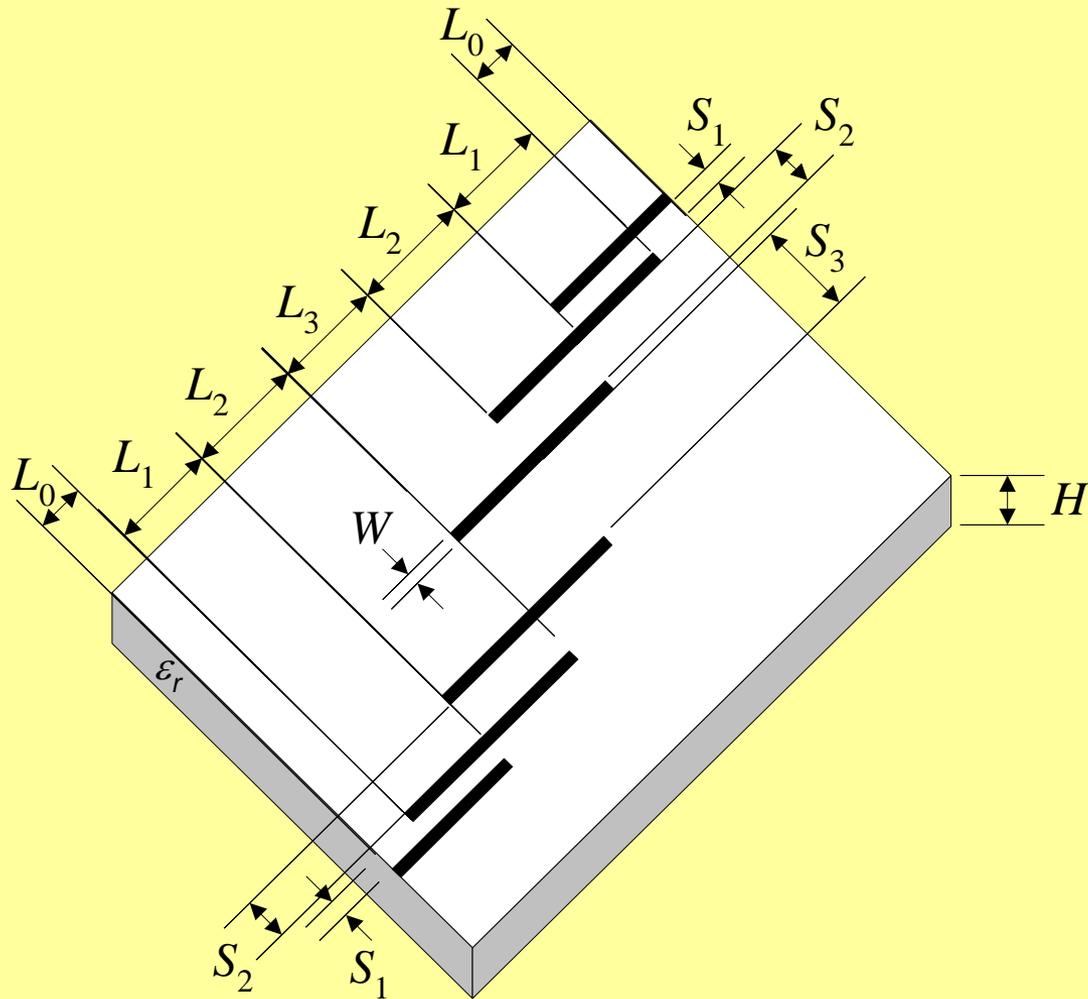
FSMN Model Results for the Right Angle Bend

comparison between *em*TM and the FSMN model





HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter (Westinghouse, 1993)





SM Based Neuromodeling of the HTS Filter

region of interest

$$175\text{mil} \leq L_1 \leq 185\text{mil}$$

$$190\text{mil} \leq L_2 \leq 210\text{mil}$$

$$175\text{mil} \leq L_3 \leq 185\text{mil}$$

$$18\text{mil} \leq S_1 \leq 22\text{mil}$$

$$75\text{mil} \leq S_2 \leq 85\text{mil}$$

$$70\text{mil} \leq S_3 \leq 90\text{mil}$$

$$3.901\text{GHz} \leq \text{freq} \leq 4.161\text{GHz}$$

$$L_0 = 50\text{mil}$$

$$H = 20\text{mil}$$

$$W = 7\text{mil}$$

$$\epsilon_r = 23.425$$

$$\text{loss tangent} = 3 \times 10^{-5}$$

“coarse” model: OSA90/hope™
empirical models

“fine” model: Sonnet’s *em*™ with high
resolution grid

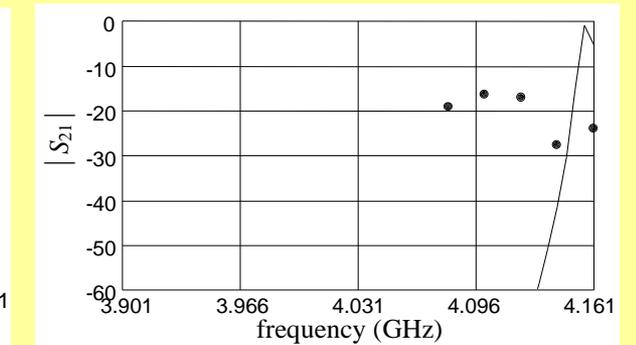
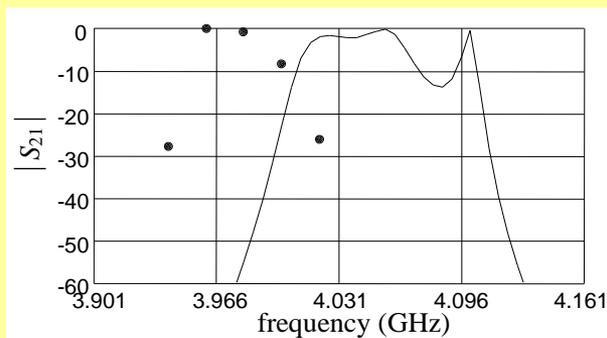
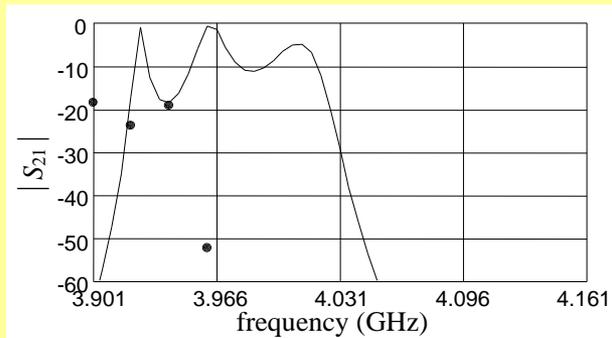
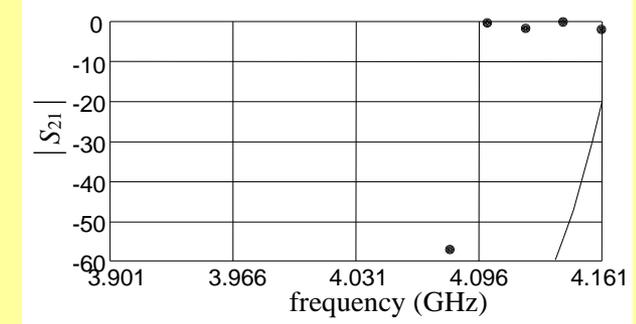
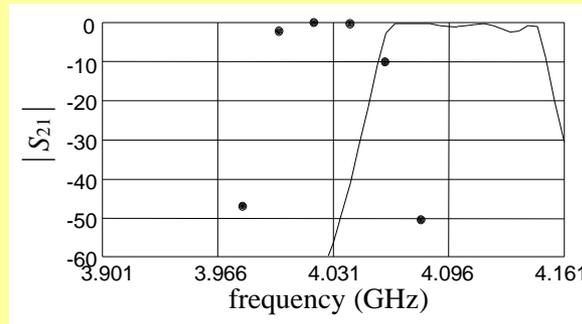
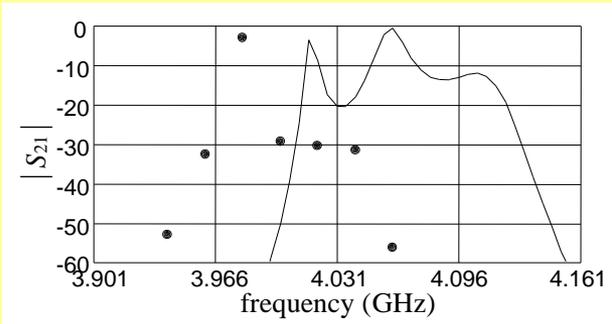
learning set: 13 base points with “star”
distribution

testing set: 7 random base points in the
region of interest (not seen in the
learning set)



HTS Filter Responses Before Neuromodeling

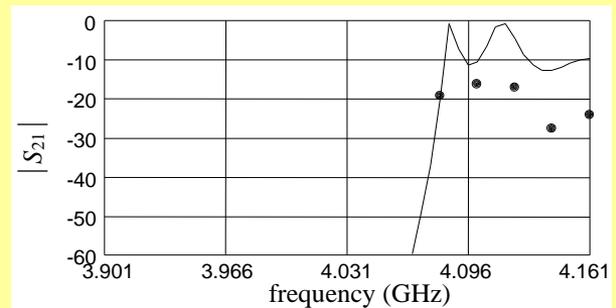
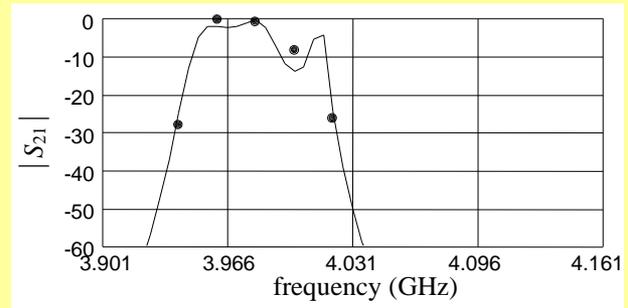
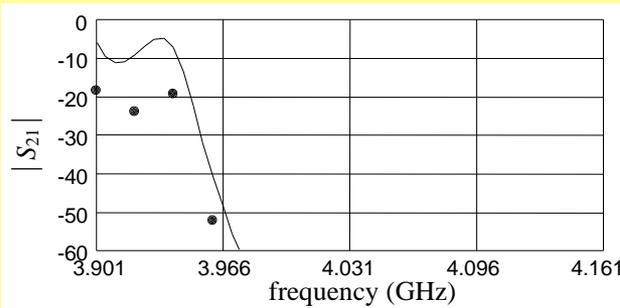
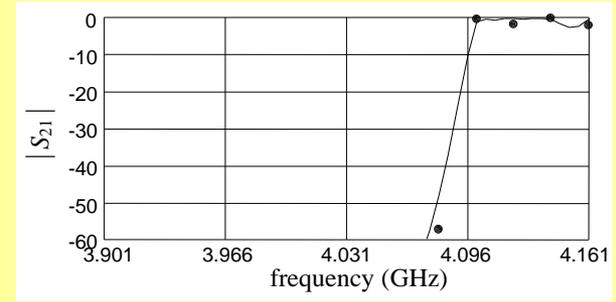
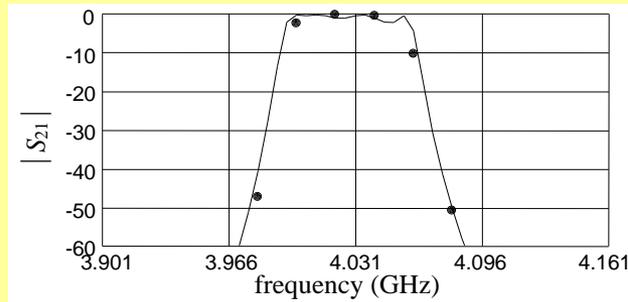
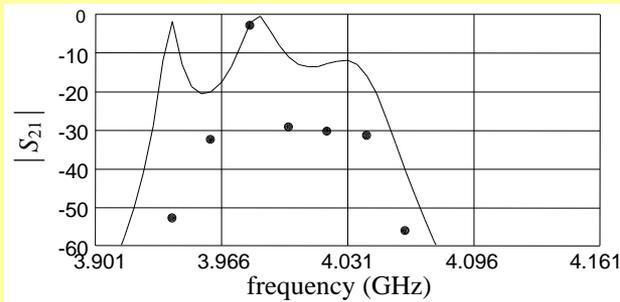
responses using *em*TM (●) and OSA90/hopeTM (—) at three learning and three test points





FMN Model for the HTS Filter (3LP:7-5-1)

responses using *em*TM (●) and FMN model (—) at the three learning and three testing points

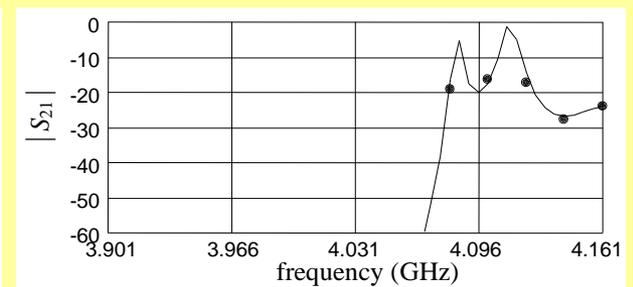
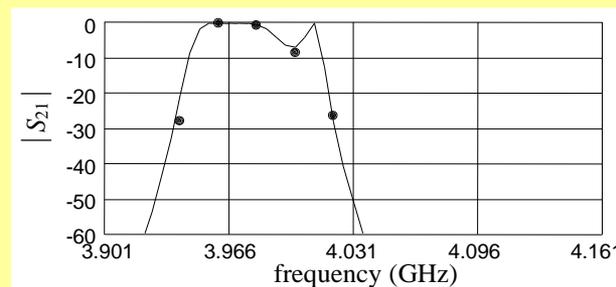
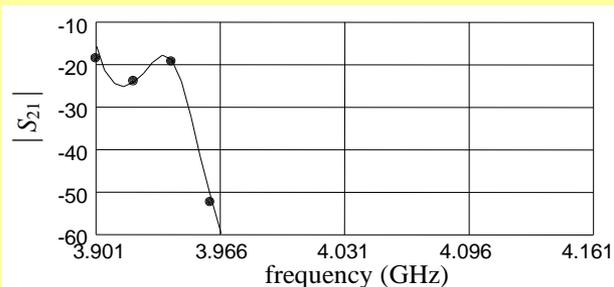
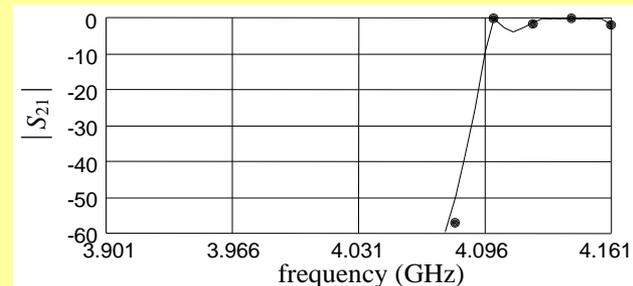
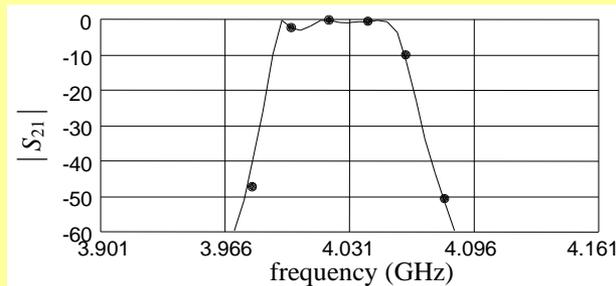
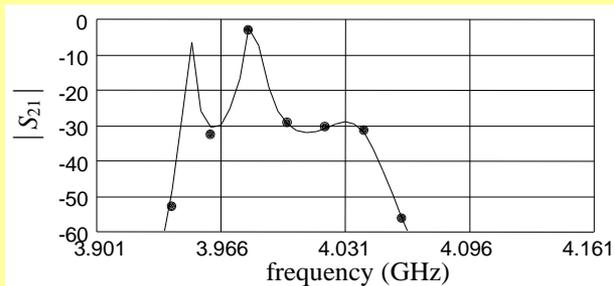




FPSMN Model Responses for the HTS Filter (3LP:7-7-3)

taking $x_c^s = [L_{1c} S_{1c}]^T$ and $x_f^s = [L_2 L_3 S_2 S_3]^T$

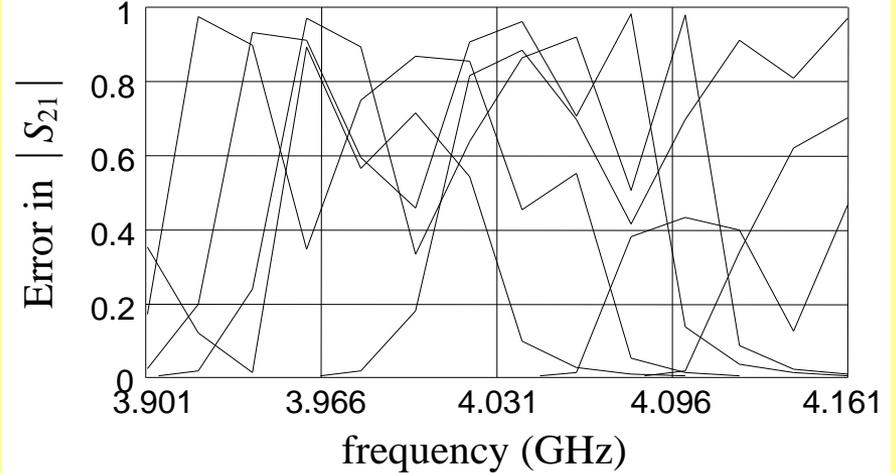
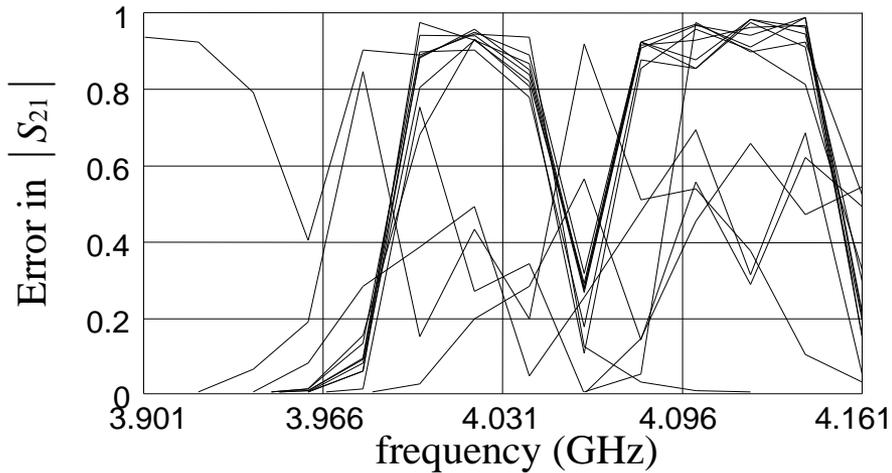
responses using em^{TM} (●) and FPSMN model (—) at the three learning and three testing points





HTS Filter Response Errors Before Neuromodeling

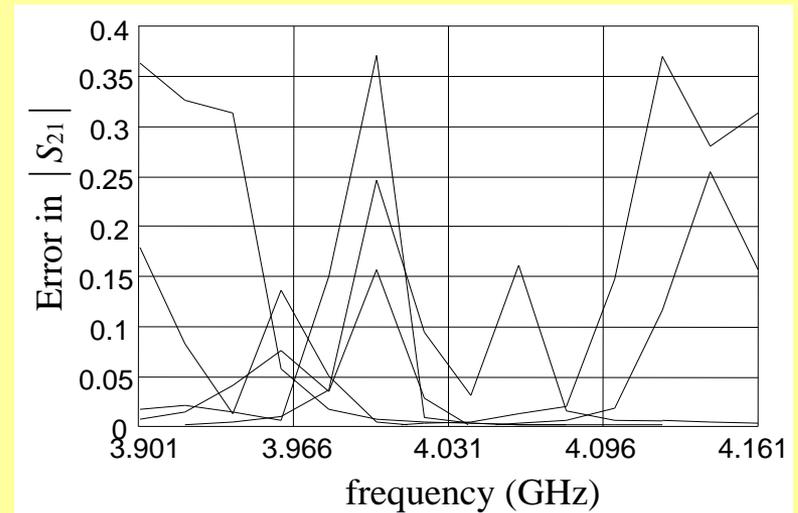
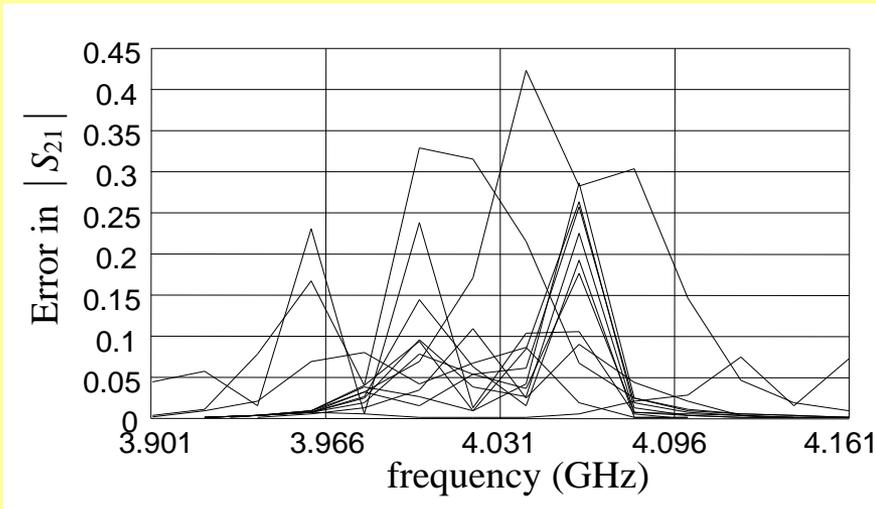
coarse model error w.r.t. *em*TM at the learning and testing sets





FMN Model Response Errors for the HTS Filter

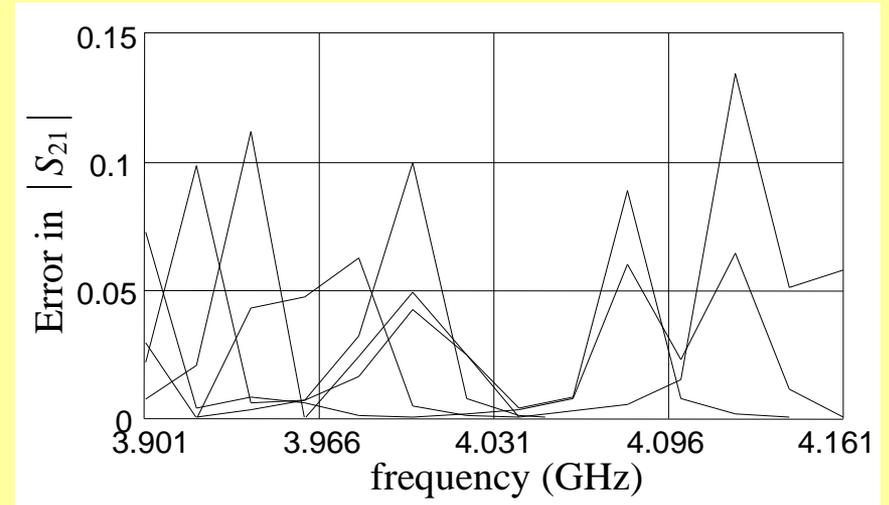
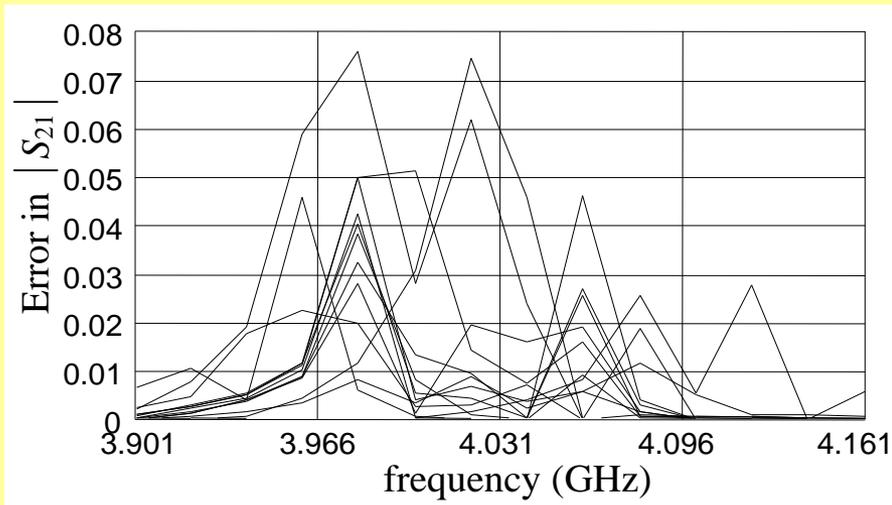
FMN model error w.r.t. em^{TM} at the learning and testing sets





FPSMN Model Response Errors for the HTS Filter

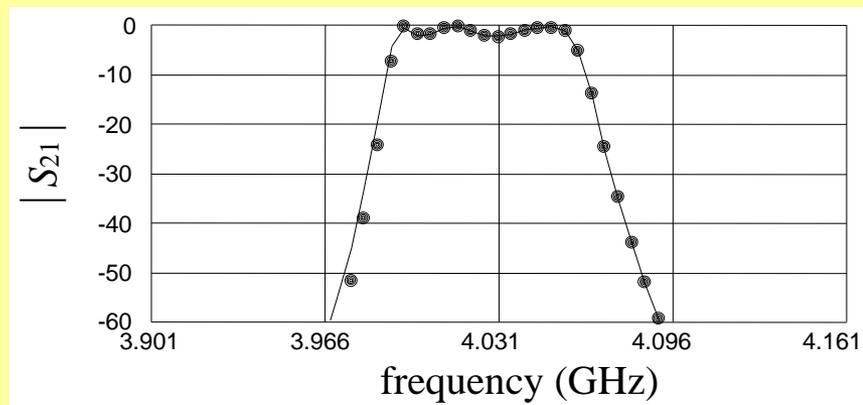
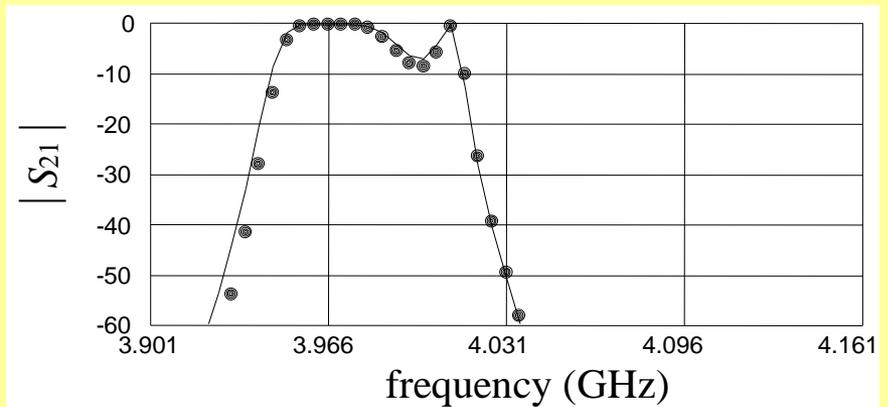
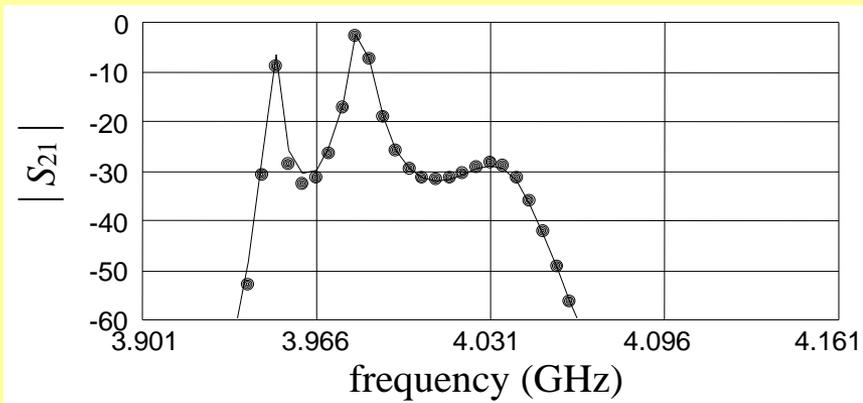
FPSMN model error w.r.t. em^{TM} at the learning and testing sets





FPSMN Model for the HTS Filter: Fine Frequency Sweep

comparison between *em*TM (●) and FPSMN model (—) at two learning and one testing points

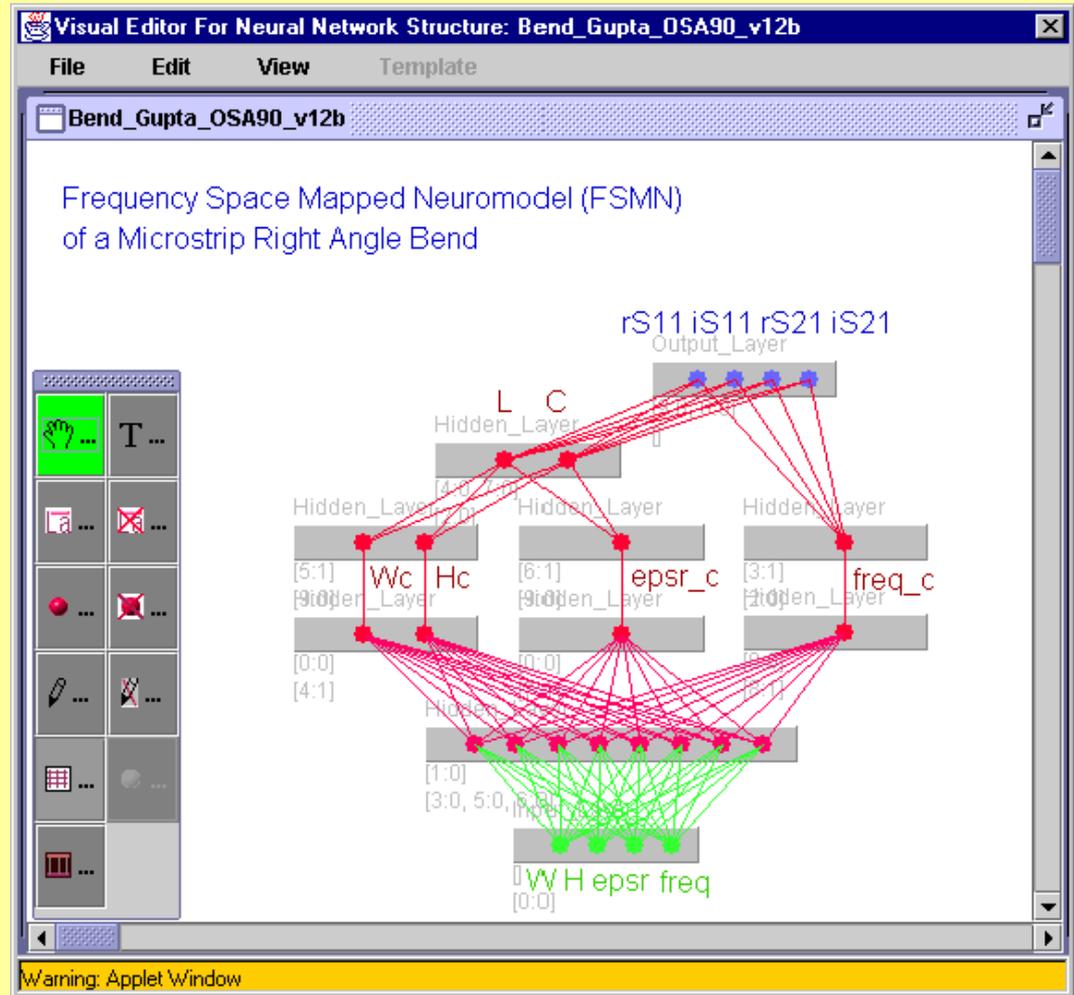




New Realizations in NeuroModeler

SM based neuromodels of several microstrip circuits have been developed using NeuroModeler Version 1.2b (1999)

they are entered into HP ADS Version 1.1 (1999) as library components through an ADS plugin module





Conclusions

we present novel applications of Space Mapping technology to the neuromodeling of microwave circuits

five powerful SM based neuromodeling techniques are described and illustrated

these techniques

- exploit the vast set of empirical models already available

- decrease the fine model evaluations needed for training

- improve generalization ability

- reduce complexity of the ANN topology

w.r.t. the classical neuromodeling approach

frequency-sensitive neuromappings expand the usefulness of empirical quasi-static models

FMN effectively aligns frequency-shifted responses

Huber optimization efficiently trains the neuromappings